RELATIONSHIPS BETWEEN HIGHWAY CAPACITY AND INDUCED VEHICLE TRAVEL

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ABSTRACT

The theory of induced travel demand asserts that increases in highway capacity will induce additional growth in traffic. This can occur through a variety of behavioral mechanisms including mode shifts, route shifts, redistribution of trips, generation of new trips, and long run land use changes that create new trips and longer trips. The objective of this paper is to statistically test whether this effect exists and to empirically derive elasticity relationships between lane miles of road capacity and vehicle miles of travel (VMT). An analysis of US data on lane mileage and vehicle miles of travel (VMT) by state is conducted. The data are disaggregated by road type (interstates, arterials, and collectors) as well as by urban and rural classifications. Various econometric specifications are tested using a fixed effect cross-sectional time series model and a set of equations by road type (using Zellner's seemingly unrelated regression). Lane miles are found to generally have a statistically significant relationship with VMT of about 0.3 to 0.6 in the short run and between 0.7 and 1.0 in the long run. Elasticities are larger for models with more specific road types. A distributed lag model suggests a reasonable long-term lag structure. About 25% of VMT growth is estimated to be due to lane mile additions assuming historical rates of growth in road capacity. The results strongly support the hypothesis that added lane mileage can induce significant additional travel.

INTRODUCTION

The theory of induced growth in vehicle travel hypothesizes that increases in the carrying capacity of a specific highway corridor or road network will attract increased levels of vehicle traffic. This economic interpretation of travel demand would argue that cost does influence demand for travel. These costs include both the capital costs of a vehicle plus fuel and maintenance costs, as well as the relative travel time costs within a given network. Increases in highway capacity should reduce the cost of travel if relative travel times are reduced, resulting in an overall increase in demand. This phenomenon of induced demand due to capacity expansions is analyzed in this paper.

From an economic perspective this would be a trivial argument. However, the demand for transportation has historically been characterized as a derived demand; that is, households only demand transportation in the course of carrying out other economic activities and not for the pleasure of movement in and of itself. From this assertion it follows that household demand for vehicle travel is only determined by demand for exogenous economic activities, and the cost of travel is considered virtually irrelevant. While this is obviously an extreme interpretation, the consideration of travel as a consumed economic commodity has not influenced overall U.S. transportation policy.

The theory of induced growth in vehicle travel has been periodically cited in the literature for many years. Goodwin (1996) cites at least one report dating back to 1938 that documented evidence for this effect. Since then the discussion of induced vehicle travel has been periodically debated and generally been discounted or considered a minor effect by policy makers. The recent SACTRA (1994) report in the United Kingdom changed much of this debate and was an acknowledgement by the U.K. government that many road projects generate extra traffic.

In the U.S. the debate on induced travel remains controversial. The debate is generally between the environmental community and traditional transportation decision makers. Much of the effort and debate has focused on the modeling procedures used in regional travel demand forecasting (Coombe, 1996; Mackie, 1996). These models are recognized as generally not being able to account for various induced travel effects. Minor upgrades to current modeling practice, such as recalibrating trip distribution models based on changes in travel speeds and inclusion of mode choice and route choice procedures can account for some of the increase in vehicle miles of travel (VMT). However, these modifications would not measure changes in trip generation (U.S. DOT, 1996) or any impact of long run land use changes. Activity based modeling approaches can also better track trip chaining behavior and the selection of non-motorized modes resulting in better model calibration than current practices (U.S. DOT, 1995).

The Transportation Research Board (TRB) recently documented the evidence for induced travel and concluded that there is some effect but was inconclusive on whether this implied any impact on the environment, especially air quality (Transportation Research Board, 1995). This study concluded that restraining growth in highway capacity would result in minor, if any, improvements in air quality. The conclusions of the TRB committee suggest that pricing and land use policies are more effective at achieving long run impacts at improving air quality compared to a policy of restraining growth in road capacity. However, land use strategies can be undermined by the construction of new highway capacity and pricing policies are to some extent an acknowledgement that induced demand is a major problem (and is one of the responses being considered in the U.K.).

The debate over induced travel has largely centered around the potential increased social costs from generated traffic. Another perspective is to consider the social benefits derived from shortening trip times and allowing more people to travel when and where they want. The US Federal Highway Administration is updating their Highway Economics Requirement System to account for these effects and to measure both the net social benefits and social costs of generated traffic. Another perspective is that roads are built with the specific intent of inducing traffic (that is, if the road won't generate traffic, then why build it?). Highway planners who argue that the goal of building new capacity is congestion reduction are implicitly not considering these arguments. When analytical models do not fully account for induced travel effects they will show that new facilities reduce congestion.

The benefits of new capacity are, however, not necessarily associated with reductions in relative travel times or increased mobility via generated trips. Long run effects may tend to outweigh these short run benefits via changes in land use patterns. In theory, increased accessibility will be capitalized into the value of land. Therefore the benefits of capacity expansion projects will fall on current land owners who enjoy increased accessibility to their land. Whether this is beneficial to society or not is beyond the scope of this paper and the present analysis, although the results presented here imply that long run effects are likely to severely diminish any short run travel time benefits.

As this discussion implies, the implications for national transportation policy of recognizing induced demand are significant and go far beyond the implications on only air quality and other environmental costs. What are the implications for funding of highways and major roads? What should the national role in highway funding be? How is general economic growth affected by changes in highway subsidies? What are the land development impacts of changes in policy? Boarnet (1997) provides an interesting discussion of some of these issues with regard to highway financing.

The analytical work presented in this paper uses an aggregate approach to analyze the issue of how highway lane-mile additions can increase total VMT. This work is similar to the work of Hansen and Huang (1997) who used California data to statistically estimate the impact of new lane-miles on VMT. Hansen and Huang (1997) found results that suggest elasticities of VMT with respect to lane-miles of up to 0.9 in the long run. The SACTRA (1994) study suggested elasticities of up to 1.0. The analysis presented here uses aggregate state level time-series data to determine relationships to VMT. The results of this study are within the ranges of previous research with short-run elasticities of about 0.5 and long run elasticities of about 0.8.

This paper is organized as follows. First, the economics of induced demand are briefly reviewed and outlined. This is followed by a discussion of the modeling frameworks employed, the data used, and analytical results. Forecasts of induced demand effects are presented followed by a concluding section that discusses potential policy implications for both federal and state transportation policy.

INDUCED TRAVEL: THEORY AND DEFINITIONS

The underlying theory behind induced travel is based upon the simple economic theory of supply and demand. Any increase in highway capacity (supply) results in a reduction in the time cost of travel. Travel time is the major component of variable costs experienced by those using private vehicles for travel. When any good (in this case travel) is reduced in cost, demand for that good increases. The analysis presented here uses lane miles as a proxy for the cost of travel. However, other policies can also reduce travel time costs and may also induce increases in VMT. These include, amongst others, traffic signal coordination, increased transit service, and other travel demand management policies that do not raise aggregate travel costs.

Travel supply and demand and the induced travel effect is illustrated graphically in Figure 1. The line S1 is supply before a capacity expansion or other changes that lower the cost of travel. The line S2 is supply after the change in capacity. S2 is shifted downward to show that the same demand is met at a lower cost. The figure shows that the quantity of travel increases as the change in supply lowers the cost from P1 to P2 of a given amount of travel. Figure 1 assumes no change in underlying demand. For example, population growth is not depicted in Figure 1. The increase in the quantity of travel from Q1 to Q2 represents the induced travel effect.

In measuring this effect there are many confounding factors that also drive growth in VMT. Population growth and demographic effects, such as increased numbers of women in the workplace, are often cited. Figure 2 shows how these effects can be graphically illustrated. The demand curve shifts outward from D1 to D2 because more travel is demanded at a given price when population increases in an area. The demand and supply curves shift simultaneously in Figure 2, and the resulting quantity of travel increases even more than in Figure 1 (to Q3). Empirically, it is difficult to isolate these two concurrent effects, and this is what causes some of the uncertainty about the magnitude of the induced travel effect, as distinct from the growth effect. In Figure 2, the induced travel effect is measured along the horizontal axis as the difference between Q2 and Q1, while the effect from exogenous growth is the difference between Q3 and Q2.[1]

Much of the debate over induced travel and its impact has often been confused by disagreements over its definition. For example, some would argue that only direct behavioral changes that generate new trips should be called induced travel. Others may claim that shifts between modes do not generate new trips and therefore can not be called induced travel (despite the increase in VMT). The definition adopted here seeks clarity in these concepts by broadly defining induced VMT as any infrastructure change that results in either short run or long run increases in VMT. Hills (1996) provides a useful categorization of the various behavioral effects one can expect from highway upgrades or capacity expansions. This was used by the SACTRA (1994) study to also define induced travel very broadly.

Different behavioral effects can be expected in the short run and in the long run. Short run effects that occur include changes in travel departure times, route switches, mode switches, longer trips, and some increase in trip generation. Of these, mode switches and new trips clearly contribute to induced vehicle travel. The inability of increased capacity to reduce congestion is most visible during peak travel times and is due to travelers shifting to preferred departure times. This effect does not represent increased VMT and so would not represent induced travel.[2] However, shifts to the peak that free up capacity at other times of the day can result in new trips being made at those times that are now less congested. Route switching can result in either shorter or longer distances being traveled. If the net effect is more travel this is clearly defined as induced VMT. If speeds are now faster, some additional long trips (perhaps recreational in nature or to more distant shopping centers) are likely to be taken and clearly represent induced travel.

Longer run effects are related to how land use patterns adjust to the newly available capacity and the resulting spatial allocation of activities. If speeds are higher, many residences and businesses will tend to relocate over time often resulting in longer

[1] The relative scale of the effects in Figure 2 do not necessarily represent actual magnitudes.

[2] Peak shifting that does not noticably reduce aggregate travel times does suggest that the benefits of most projects are not accurately assessed. Rather than assessing benefits based on travel times an assessment based on the ability to travel at a preferred time should be done (Small, 1992).

distance trips (Gordon and Richardson, 1994).[3] The concentration of retail activities in "big box" stores or auto-dependent regional shopping centers (rather than centrally located business districts) further increases VMT. These are longer run effects that can be included in the definition of induced travel since they are the result of economic changes induced by capacity additions.

MODELING APPROACHES AND RESULTS

A variety of alternative statistical modeling approaches are presented to explore the relationships between lane miles of road capacity and vehicle miles of travel. These are aggregate econometric models of VMT and lane miles. In contrast, SACTRA (1994) used a case study approach of before and after data for a wide selection of projects. Another technique would be to use regional travel demand models or activity-based models. These use individual level disaggregate data from which models of individual behavior can be developed. While a disaggregate approach is normally used for project specific analysis, the aggregate econometric approach adopted here provides useful information on total system effects.

VMT and Induced Travel Modeling Issues

Many different factors effect total growth in VMT. Population growth naturally drives total VMT to higher levels. Total VMT in the U.S. grew by 3.2% annually between 1970 and 1993 (DOE, 1995) exceeding total population growth (which was about 0.9% annually). Many other demographic factors have also been the cause of recent growth in VMT. These include, among others, increases in employment levels, increased female participation in the work force, and smaller household sizes. These are all highly correlated with population increases and therefore their impacts cannot be separated from overall trends in population growth. Population by state should serve as an adequate proxy for many of these demographic effects. Another factor influencing VMT growth is the increase in vehicle licensing rates and the saturation of vehicle ownership in the U.S.

[3] While the work of Gordon and Richardson is generally meant to extoll the virtues of suburban land development patterns, their analysis of stability in work travel times while travel speeds increase, provides good empirical evidence for induced travel.

The 1995 Nationwide Personal Transportation Survey (U.S. DOT, 1997) results show that only 8 million U.S. households do not own a motor vehicle and over 40 million households own two vehicles. This variable is not used in the analysis due to high collinearity with population. Changes in per capita income also affect total VMT (and is a significant factor as discussed in the following sections).

The total cost of travel plays a role in demand for vehicle travel and is the basic premise of the theory of induced travel. The major factor affecting the cost of travel is the value of time associated with travel. Several studies have documented the value of travel time (Small, 1992; Waters, 1992). Goodwin (1992) reviewed elasticity estimates derived from studies based upon fuel prices. Tolls also affect total cost but are not included in the analysis due their negligible role in the U.S.

Spatial reorganization of urban areas and increased concentration of many retail activities may also be increasing VMT. The 1995 NPTS show that 77% of person-miles of travel is now for non-commute trips. Much of this increase may be related to increased decentralization and the development of more auto-dependent communities, which are endogenous to the development of new road capacity.

There is often confusion over how changes in road supply can affect behavior. For example, some might argue that reductions in transit usage have been a factor resulting in increased VMT, independent of changes in road supply. Other research, however, shows how reductions in transit service can occur because of increases in road supply (Noland, 1999). This effect, known as the Downs-Thomson paradox results when an increase in road supply makes traveling by auto preferable to transit alternatives. The transit agency then needs to either raise fares or reduce service; this results in a further decrease in transit usage and perhaps even worse congestion than before the capacity expansion (Arnott and Small, 1994). Changes in many other apparently socio-economic trends could, in theory, be attributed to reduced transportation costs from road expansion.

One issue that cannot be completely resolved with a statistical analysis is the issue of causality. Does VMT growth cause more lane miles to be built or does capacity expansion induce VMT? The analysis presented here strongly supports the hypothesis of induced travel. The use of a fixed effects cross-sectional time series model minimizes any simultaneity bias in the data (although it does not necessarily eliminate it). An ideal technique for resolving the causality debate would be to use an instrumental variables approach. If another variable can be found that is correlated with lane miles, but is orthogonal to VMT, then this would be possible. Several variables were explored during the course of this research in an attempt to find an appropriate instrument. However, all the variables that may correlate with lane miles also tend to be correlated with VMT.[4] Regardless of these limitations, the overall robustness of the results (presented below) using different formulations of the model, support the hypothesis of induced travel.

Many transportation professionals will argue that induced travel only demonstrates that highway planners have put the roads where people want to travel, that is, they have made accurate forecasts. Or alternatively, induced travel provides benefits since people obviously want to travel. These benefits must be weighed against any social costs associated with the new capacity. This is beyond the scope of the current paper but is certainly a rich area for future research.

Data

To empirically measure induced travel effects it is necessary to separate the influences of the various factors driving VMT growth. To isolate the impact of road supply, i.e., lane miles, several models are formulated. The data is a cross-sectional time series (panel data) of the 50 U.S. states between the years 1984 – 1996. The District of Columbia is omitted from the data set since it does not have the characteristics of a typical state and was an obvious outlier. Delaware was omitted from the simultaneous equation models since it did not have one category of road type (rural interstates). The data for VMT and lane miles for each state over the 13 year period was collected from the Highway Statistics series published by the Federal Highway Administration (for example, see U.S. DOT; (1997b)).

Total lane mile growth over this 13 year period has only been about 1.25% and total route miles grew by about 0.71%. Excluding local roads these figures are about 3.13% and 1.73% respectively. About one quarter of new lane miles is from new roads while three quarters is expansion of existing roads. There are major differences between

[4] Hansen and Huang (1997) were also unable to find an appropriate instrument in their analysis.

different road categories.[5] Interstate and freeway lane miles have grown by about 8.98% of which about 16% is for new roads. Arterial lane miles have grown about 11.01% of which about 32.80% is for new roads. Collector lane miles and route miles have actually declined slightly (1.64% and 1.56% respectively), probably due to reclassification as higher or lower order roads. Despite this relatively smal growth in lanes miles (due partly to the large existing network) VMT has grown at about 3.2% per year.

Other variables included in the model include state population, per capita income by state, and the cost per energy unit (million BTUs) of gasoline (U.S. DOE, 1994).[6] The latter was based on average rates in each state for each year adjusted to constant dollars. State population is from U.S. DOC (1997a) and per capita income in real dollars is from U.S. DOC (1997b). During development of the model various other demographic variables were examined. Many of these tend to have high collinearity with population, such as state driver and vehicle licensing rates. A variety of statistical approaches, discussed below, were estimated.

General Modeling Approach

The general modeling approach estimates models of the following form:

$$\log\left(VMT_{itr}\right) = c + a_i + \sum_k b^k \log\left(X_{it}^k\right) + l \log\left(LM_{itrl}\right) + e_{it}$$

The parameters are defined as:

VMT_{itr}	= VMT in state *i*, for year *t*, by road type *r*.
c	= constant term
$\mapsto_i$	= fixed effect for state *i*, to be estimated
$\updownarrow^k$	= coefficients to be estimated (for demographic and other parameters)
[illegible]	= coefficient to be estimated for LM parameter
X_{it}^k	= value of demographic and other variables for state, *i*, and time, *t*.

[5] As defined in U.S. DOT (1997c) these are interstate highways, arterial roads (which include some controlled access highways) but are generally uncontrolled, collector facilities that collect and disperse traffic between arterials and lower grade facilities, and local roads that distribute traffic to actual destinations.

[6] Data for 1995 and 1996 were collected from the Petroleum Marketing Annual (U.S. DOE, 1997). These data do not include fuel taxes which were added from U.S. DOT(1997c).

LM_{itrl} = proxy for cost of travel time (lane miles) by state, *i*, for year, *t*, for road type, *r*, lagged by *l* years.

ε_{it} = random error term

The model is estimated with different road types as defined by U.S. DOT (1997c) and referenced above. Both VMT and lane mile data is analyzed for all road types except local roads.[7] The data was further disaggregated by urban and rural classifications. Rural roads are defined as areas with a population below 5,000, which might not strictly represent all areas usually considered rural. Some roads were obviously reclassified from rural to urban over the course of the time series.

When using lane miles as a proxy for travel cost it is necessary to lag the variable. This is needed to allow individual behavior to respond to changes in highway capacity. Hansen and Huang (1997) found that lags of about 2 to 4 years gave good results for their estimations. Another technique, discussed further below in the section on distributed lag models, is to use a model that captures both long run and short run lag effects. Long run lags should represent cumulative impacts that occur over time. Inclusion of only one lag would not capture all the impacts from multiple years.

The analysis is focused primarily on estimating the statistical significance and magnitude of the elasticity of VMT with respect to lane miles. An elasticity provides a measure of how a change in one variable (lane miles) results in a a change in another response variable (VMT). For example, an elasticity of VMT with respect to lane miles of 0.5 would imply that a 1% increase in lane miles will result in a 0.5% increase in VMT.

$$l = \frac{\partial \log(VMT)}{\partial \log(LM)} = \frac{LM}{VMT} \cdot \frac{\partial(VMT)}{\partial(LM)}$$

The elasticity is just the coefficient of the log of that variable, thus a logarithmic specification is used in the regression analysis. This is described simply as,

Where λ is the elasticity and is also the estimated coefficient in the model.

[7] Local roads make up the bulk of nationwide lane miles but relatively little of total VMT. Preliminary analysis including local roads showed they were not significant in inducing VMT. This is not particularly surprising since they are used primarily for access to destinations, not for major amounts of travel

Logarithmic transformations also minimize any heteroskedasticity in the cross-sectional data from combining states with large differences in size or population. The logarithmic transformation does not change the relative significance of the results compared to a linear formulation but does allow for an easier interpretation of the elasticity coefficients.

The model is specified as a "fixed effects" or dummy variable model (Judge et. al, 1985). Essentially the model includes a dummy variable for each state and is estimated as an ordinary least squares (OLS) model. The inclusion of a dummy variable for each state allows unmeasured factors affecting the dependent variable that are associated with each state to be controlled for. The intercept coefficient for each state is independently fixed while the slope is estimated to be the same across states. That is, this model assumes that all states respond to lane mile increases (and changes in other exogenous variables) with the same behavior. An alternative formulation known as the random effects model would allow each state to have not only a different intercept coefficient but individual slope coefficients. Selected usage of the Hausman test rejected this as a reasonable hypothesis for this model (Judge et al., 1985).

The use of both population and lane miles as independent variables can cause a multi-collinearity problem. To correct this problem, lane miles per capita are used in the following models. This reduced the largest correlations which were for urban lane miles from high values above 0.95 to virtually no correlation. Interestingly the rural lane mile per capita variables have a higher correlation with population than when not calculated as per capita variables, but the level of correlation is still not a problem. Correlations for unlagged lane mile variables and per capita lane mile variables are shown in Table 1. The growth model discussed below further eliminates most problems with multicollinearity in the independent variables.

Alternatively, one could also estimate models with VMT per capita as the dependent variable while omitting population as an explanatory variable. The general results would not differ (see, for example, Table 8). The decision was made to regress on total VMT primarily because it allows a decomposition of population effects on total

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between destinations.

VMT growth. Many critics of the theory of induced travel attribute population growth and demographic change as being the only factors driving VMT growth. It is hoped that this analysis will resolve these criticisms of the theory.

Model 1: Aggregate Data on Road Types

The initial model estimated sums the road types and VMT to determine whether total VMT (excluding VMT on local roads) can be explained by increases in total non-local lane miles (that is, the sum of interstate, arterial, and collector lane miles). The results, shown in Table 2, show that lane miles are a statistically significant determinant of VMT, except in the model with a 2 year lag. The elasticities are about 0.25, suggesting that a 0.25% increase in non-local VMT occurs for every 1% increase in non-local lane miles. There does not appear to be a clear trend suggesting that elasticities increase or decrease when lags are modelled, though the 2 year lag model is significant at the 90% level of confidence. The estimated coefficients take into account state specific effects which would include relative levels of congestion in different states. However, this analysis did not attempt to measure differences in induced travel effects due to relative levels of congestion (see Noland & Cowart (1999) for an attempt to measure differences using data from metropolitan areas).

Population, per capita income, and gasoline cost all have the expected direction and are all highly significant. The population coefficient is generally about 1, suggesting that population growth translates into proportional VMT growth. The effect of growth in per capita income varies from about 0.85 to slightly over 1. The key point is that with population controlled for, and multi-collinearity adjusted for, one gets a highly significant effect from the lane mile variable, suggesting that the hypothesis of induced demand cannot be rejected.

The fuel cost elasticities are low compared to other results in the literature that suggest a range of about 0.2 – 0.3. As will be seen in the other models discussed below, this varies between road types. The low elasticity values may reflect the fact that post-1984 data is used and gasoline prices have varied much less during this time period than before 1984. The values are also annual averages and do not reflect seasonal variability.

Disaggregation of the data into individual road types gives larger elasticities on those specific road types and shows where induced demand effects may be greatest. Table 3 presents models of interstate, arterial, and collector lane miles with the VMT for those road types as the respective dependent variables.

This model shows a stronger relationship between the various road types and VMT on those road types. All the non-lagged and 2 year lag models have statistically significant coefficients. Arterial lane miles are also significant in the 5 year lag model. One would expect interstates to generally have the highest elasticity coefficients since they would be most effective at reducing travel times. The results do not show a clear pattern between the different road types. For example, it is surprising that collector roads have a higher elasticity (0.892) than the interstate and arterial roads. This may be due to a strong relationship between new auto dependent land development and new collector roads that serve that development.

Model 2: Simultaneous Equation Estimation

Another approach takes advantage of the interrelationships between VMT on various road types to improve model estimation using contemporaneous correlation between error terms. Behaviorally, this assumes that a given amount of VMT on a specific road type will effect the amount of VMT on another road type. For example, if one assumes that individuals have a time budget for the amount of travel they undertake per day, then their allocation of VMT to different road types will be inter-related.[8] A system of equations, one for each road type, can be estimated using Zellner's seemingly unrelated regression (see Pindyck & Rubinfeld (1981) for a detailed derivation of the estimation procedure in matrix form).

The disturbance covariance matrix in this model is assumed to be non-diagonal because of the relationships between the equations. This technique produces lower standard errors by taking advantage of the contemporaneous correlation between the error terms. In other words, the error term associated with an equation estimated for a specific

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[8] Alternatively, one could analyze the impact of lane miles of one road type on VMT on another road type. For example, do more freeways generate additional VMT on arterial roads? This is a rich area for further research with this database, which has been suggested by several reviewers.

road type (e.g. urban interstates) is correlated with the error term for rural arterials. This information allows a more efficient estimator for the coefficients to be derived.

Results are shown in Table 4. Coefficient values for the lane mile parameters are generally larger and show increased statistical significance. Both the model with no lag and with the 2 year lag show that all increases in lane miles are related to an increase in VMT (all are statistically significant at the 95% confidence level). The no lag interstate lane mile coefficient shows an elasticity of 0.713, the arterial no lag model has an elasticity of 0.690, and the collector no lag model has an elasticity of 0.826. The elasticity values are smaller in the 2 year lag model. The elasticities are 0.567, 0.267 and 0.509 for interstates, arterials, and collectors respectively. Other than for arterials, the 5 year lag model lane mile coefficients are not significant.

This model would seem to suggest the largest immediate and short term (up to 2 years) effect from adding interstate and collector lane miles. On the other hand, while arterial lane miles seem to generate less VMT, the effect persists over a longer time period (at least up to 5 years). There may be some intuitive reasoning behind these results. First, new construction and expansion of interstates may result in large immediate effects from relatively large reductions in travel costs. Construction of collector lane miles may mirror the construction of new developments that they may serve, also generating some immediate increases in VMT. Arterials, on the other hand, may respond slower as land use patterns respond to lower travel costs on arterials. These are, of course, merely speculations as to what may be driving differences in the coefficient values, but do suggest areas where more detailed analysis could be pursued.

The other coefficients also show some interesting effects. The fuel cost coefficient is generally significant with a negative sign. It is largest for the interstate VMT models, somewhat lower for the arterial VMT models, and much lower for the collector VMT models. The longer distances travelled on interstates probably accounts for the larger elasticity of fuel costs with respect to interstate VMT. These trips may be more discretionary or have substitutes (such as shorter trips to local destinations). Collector roads, which are not used for longer distance travel show the smallest fuel cost elasticity, and may reflect the less discretionary travel involved in access to destinations.

The same elasticity difference is apparent with respect to per capita income. Per capita income generally has an elasticity greater than (or nearly equal to) one with respect to interstate VMT. Increases in income may result in more leisure travel (on interstates) and longer commuting distances (on interstates) as people move to more distant suburbs.

A further disaggregation of the data can be achieved by breaking out urban and rural VMT and lane miles for each road class. The simultaneous equation model for this set of six equations is shown in Table 5 with no lag and in Table 6 for a 5 year lag. The rural road categories have relatively high collinearity which may somewhat bias the results on these coefficients. The no lag model shows very large elasticities for all the lane mile variables. They range from a low of 0.325 for rural interstates up to 0.773 for rural collectors. The urban lane mile elasticities are all above 0.7. The 5 year lag model (Table 6) shows significance only for urban interstates and arterials and rural arterials. Surprisingly the rural interstate coefficient is negative, although it is below the 90% level of significance. Overall these results demonstrate a strong induced travel effect with some differentiation between different road types that merits further investigation.

Model 3: Distributed Lags

The previous models suggest that the short term elasticity of lane miles with respect to VMT is greater in the first year than for subsequent years. However, in theory, one would expect a cumulative impact where the increase in VMT adjusts over time. The previous models only estimate a single lag and do not take into account this cumulative impact.

One technique for estimating a long term elasticity is a distributed lag model using a lagged dependent variable (Johnston, 1984). This technique, known as partial adjustment, has been applied to shocks in the price of gasoline and its effect on consumption over time. In the short run, gasoline consumption is reduced by cancellation of some trips and shorter trips, while in the long run fuel efficiency is increased. The case of increased road capacity has some parallels in that the adjustment process is hypothesized to take place over time with both short run and long run effects. This technique is relatively simple to apply but does assume that the adjustment process from the other independent variables, population, personal income, and gasoline prices, is the same as for lane mileage. It also assumes an exponential pattern to the lag, which may be fairly realistic in this case.

The specification for the distributed lag model is:

$$\log(VMT_{itr}) = g\,\log\left(VMT_{i(t-1)r}\right) + c + a_i + \sum_k b^k \log\left(X_{it}^k\right) + l\,\log(LM_{itr}) + e_{it}$$

All variables are as defined previously. The only difference is the lagged VMT term with a coefficient γ.

Short run elasticities of lane miles with respect to VMT correspond to the coefficient on the lane mile variable, λ. Long run elasticities can be calculated as

$$h = \frac{l}{1-g}$$

The adjustment parameter, γ, is the coefficient on the lagged VMT variable as defined above (Johnston, 1984).

Distributed lag models were estimated with both aggregate VMT and lane mile data and with simultaneous equations disaggregated by road type. Table 7 shows two aggregate distributed lag models. One problem with including lagged VMT is that it is collinear with population and lane miles. The first model in Table 7 includes population despite this problem. The second model removes population and has VMT per capita as the dependent variable. The coefficient estimates do not appear to be effected by the collinearity. The elasticities for the two estimated equations are generally similar. Long run elasticities are substantially larger than the short run elasticities as one would expect.

Tables 8 and 9 present two similar analyses using a simultaneous equation framework. Table 8 omits population as an independent variable and uses VMT per capita as the dependent variable. Table 9 includes population and VMT as the dependent variable. Lagged VMT is highly collinear with population, however the similarity of the coefficients with and without the population variable suggest that multi-collinearity is not creating a large bias in the model in Table 9. Both these models have large long run elasticities in the 0.7 – 1.0 range (exceeding 1.0 for collector roads). Short run elasticities are also substantial, in the range of 0.2 - 0.5. Short run elasticities are larger for urban road categories than for rural roads, perhaps due to more congestion in urban areas. Long run elasticities are about the same for both urban and rural roads. This would suggest that capacity increases are triggering fundamental land use changes that increase VMT in both urban and rural areas. Similar to some of the other models, collector roads again have relatively large elasticities (exceeding 1.0 for the long run elasticities). This may imply a strong relationship between adding collector roads and subsequent new development that generates new trips. Rural interstates have the smallest short run elasticities. This suggests that long distance travel does not respond as quickly to capacity increases (or that rural interstates are less congested).

Population is also a significant factor with larger coefficients in the urban equations. Per capita income is significant across equations with smaller coefficients on collector roads. This may suggest some base level of travel that is not related to income while the use of interstates and arterial roads is affected more by income levels. Gasoline price coefficients are generally small. They are insignificant for collector roads, again suggesting that base VMT is unaffected by gasoline prices.

These results are similar to the results of Tables 5 and 6. However, the previous method that incorporated only one 5 year lag did not fully account for the cumulative impact of long term effects as this method does. The distributed lag models also have smaller coefficient values on the demographic variables since they are short run effects. The long run elasticities for these correspond fairly closely with the estimates in Tables 5 and 6.

One criticism of distributed lag models is that they are highly unstable in providing good predictions. Almon (1989) suggests a procedure for comparing the actual values with predicted values over the sampling period. Forecasts of VMT are calculated for each year using the data for each year plus a forecasted lagged value of VMT. Figure 3 shows a very good fit for the model in Table 9 between predicted total VMT and actual total VMT. Rural and urban collector predictions are the least stable (comparatively) but represent a minor fraction of the total VMT.

Model 4: Growth model

A technique for eliminating the multicollinearity between the independent variables is estimation of a growth or difference model. The specification estimates the percent growth in VMT as a function of percent growth in lane miles and the other independent variables. Correlation is essentially eliminated as a problem between the lane mile and population variables. Table 10 shows the correlations between the difference in lane miles (by road type) and the population difference variables. This eliminates one potential problem with the previous model specifications. The model can be specified as the difference between logs of the variables:

$$\log(VMT_{itr}) - \log(VMT_{i(t-1)r}) = c + a_i + \sum_k b^k \left(\log\left(X_{it}^k\right) - \log\left(X_{i(t-1)}^k\right)\right) + l\left(\log(LM_{itr}) - \log(LM_{i(t-1)r})\right) + e_{it}$$

This corresponds to percent growth in the dependent and independent variables.

The growth model also allows the testing of changes in lane miles between different years and how that might affect current changes in VMT. This was done for lags between two and up to five years, but no significant results were found. Table 11 shows results for a fixed effect difference model estimated as a set of seemingly unrelated regressions. This is done with no lag which was the only formulation that provided a significant effect. The results are consistent with previous specifications and add support to the robustness of the relationships.

IMPORTANCE OF THE INDUCED DEMAND EFFECT

While the above results clearly demonstrate that induced travel is a likely outcome of capacity expansion, many critics have asserted that demographic factors are still the overwhelming factor in driving increases in VMT. For example, Heanue (1998) uses the elasticity values generated by SACTRA (1994) and Hansen (1995) and calculates that capacity expansion accounts for somewhere between 7% and 22% of VMT growth. The conclusion reached by the author is that while it is necessary to account for this in investment decisions and cost-benefit analysis the overall importance of induced demand is minor. One can certainly argue whether a factor that may cause up to 22% of VMT growth should be considered minor, but arguments of this type tend to obfuscate the issue. The key question is the relative social costs and benefits of the additional VMT.

To address this question, the relative contribution of lane mile additions to VMT growth, relative to other factors is analyzed for some of the models above. The models estimated in Table 5 (fixed effects SURE model), Table 9 (distributed lag model), and

Table 11 (growth model) are forecasted out by 5 years (from 1996-2001) for three different scenarios. The first scenario assumes that the growth rate in demographic variables (personal income, population, and gasoline costs) and lane miles by road type follows historical trends between 1992-1996. A second scenario assumes growth only in lane miles and no growth in the demographic variables while the third assumes no growth in lane miles but historical growth in the demographic variables.

Results for each of the models are shown in Tables 12, 13 and 14. Note that for the distributed lag model an iterative process to generate new lag values was needed to calculate the forecast value. The full results are displayed in Figure 4 and in Table 13.

These results are quite interesting. First, it is clear that if lane mile growth is frozen, then demographic growth continues to drive increases in total VMT. The opposite is also true that if lane mile growth continues but demographic growth is frozen, VMT still continues to grow but not as much. The annualized rate of total VMT growth (assuming historical growth in both variables) ranges from 2.65% to 2.92% for the three models. With only lane mile growth it is ranges from 0.79% to 1.73% annualized VMT growth over 5 years. With just demographic growth the range is from 1.89% to 2.31% annualized VMT growth over 5 years. The difference between this latter growth and the scenario with growth in all the variables can be attributed to additional capacity. Therefore, if capacity is frozen at current levels, annualized VMT growth after 5 years will be between 0.61% and 0.76% less than compared to current trends. This also indicates a fairly robust effect for the different model specifications. The distributed lag model forecast (see Table 13) shows both a short run (0.65% less in the first year) and long run effect (0.76% less after five years). For the distributed lag model about 28.7% (0.76/2.65) of total VMT growth can be attributed to growth in capacity over 5 years. In the first year induced demand accounts for 23.7% (0.65/2.74) of VMT growth in this model. For the model in Table 5 induced demand causes 21% of VMT growth and for the model in Table 11 it accounts for 26.5% of VMT growth.

The induced growth in VMT also has a substantial effect on total vehicle emissions. If we assume that 28% of the growth rate in VMT is attributable to lane miles (as estimated in the distributed lag model), this amounts roughly to about about 43 million metric tons of annual carbon emissions in the year 2012. This is nearly half of the targeted carbon emissions reduction estimated for the U.S. Climate Change Action Plan of 90 million metric tons of carbon (by 2010). It is also equivalent to a policy of increasing the light duty vehicle fleet efficiency (for gasoline) by about 2.5% annually between 1999 and 2012 to over 47 miles per gallon. This would be virtually impossible to implement even with the immediate introduction of new fuel efficient vehicle technologies.[9]

This estimate of carbon emissions does not account for changes in levels of congestion and traffic flow dynamics that may also effect emissions. Emissions of criteria air pollutants (NO_X, CO, and HC) tend to be more sensitive to these dynamics than carbon emissions. A more detailed analysis would look at changes in these dynamics due to exogenous growth in VMT not related to induced effects. However, it is also possible that relative traffic flow dynamics will be equally bad but with more traffic if additional capacity is built.

Overall, these results suggest that if the induced travel effect is accounting for a quarter of VMT growth, that this is a highly significant effect that needs to be measured in any defensible benefit cost analysis or travel demand modeling exercise.

CONCLUSIONS

The results of the analyses presented clearly demonstrate that the hypothesis of induced demand cannot be rejected. Increased capacity clearly increases vehicle miles of travel beyond any short run congestion relief that may be obtained. The methods employed all found statistically significant relationships between lane miles and VMT. While other factors, such as population growth, also drive increases in VMT, capacity additions account for about one quarter of this growth. This contribution to VMT growth has significant impacts on various environmental goals. For example, increasing U.S. highway capacity at historical rates may result in up to 43 million metric tons of carbon emissions compared to a complete freeze on adding additional lane miles. Constructing new lane miles at half the current rate might reduce carbon emissions proportionally.

[9] These estimates are based on forecasts in U.S. DOE/EIA (1998). The VMT forecasts in this report are generally considered conservative by EPA which uses a 2.3% annual growth rate rather than EIA's

The different statistical approaches estimated gave a range of values for elasticity estimates. In general, more disaggregate data by road type led to relatively greater elasticity values for VMT. This is not a surprising result as many countervailing effects may be present in a more aggregate analysis and the simultaneous equations may be picking up diversion effects between road categories. Hansen and Huang's (1997) study found higher elasticities (up to 0.9) than the analyses presented here which may be due to the more localized data for specific California counties and metropolitan areas that they analyzed.

Another general effect is that urban roads have a greater relationship to VMT growth than smaller rural roads. This is not too surprising since these roads are probably more congested than those in rural areas and would be currently suppressing some growth in traffic if they are congested. Also, in general, the lagged models with one lag term show less significance and smaller coefficients than the unlagged model. This is consistent with an exponential lag function as modeled with the distributed lag model. Cumulative long term elasticities are greater than short run elasticities, as would be expected.

One surprising result is that collector roads often had a larger elasticity value than interstates and arterials. While this cannot be clearly explained it may be due to new developments that are built in conjunction with new collector road capacity.

The selection of estimation procedure can produce very different results. The use of fixed effects significantly reduced the level of significance compared to modeling without fixed effects (results are not shown). The latter specification would be inappropriate, but is commonly used by many practitioners. The ability to use simultaneous equations and fixed effects seems to provide robust results that take advantage of the statistical properties of the data.

Recognition of induced travel effects has several major policy implications. The major question is whether the induced growth in VMT is beneficial or not. There may be some benefits to providing mobility and increasing access to undeveloped land, however, this must be weighed against the environmental and social costs associated with increases in VMT, road construction, and land development. This latter is a major issue with regard

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annual growth rate of 1.6%. Reductions in a higher growth rate would give larger emissions benefits.

to urban development and the debate over relatively more compact versus sprawling development patterns. The ability of planners to answer these questions is hampered by travel demand forecasting techniques that cannot adequately model these impacts at either the regional or project specific level (although new innovations and techniques are beginning to be used). The other implication is that building more road capacity will, in the long run, not solve congestion problems. While the results derived here do not strictly prove a causal relationship between lane miles and VMT, these results still strongly suggest that induced demand effects are real and need to be considered both by planners and policy makers at both the regional and national level.

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Figure 1

Induced Travel

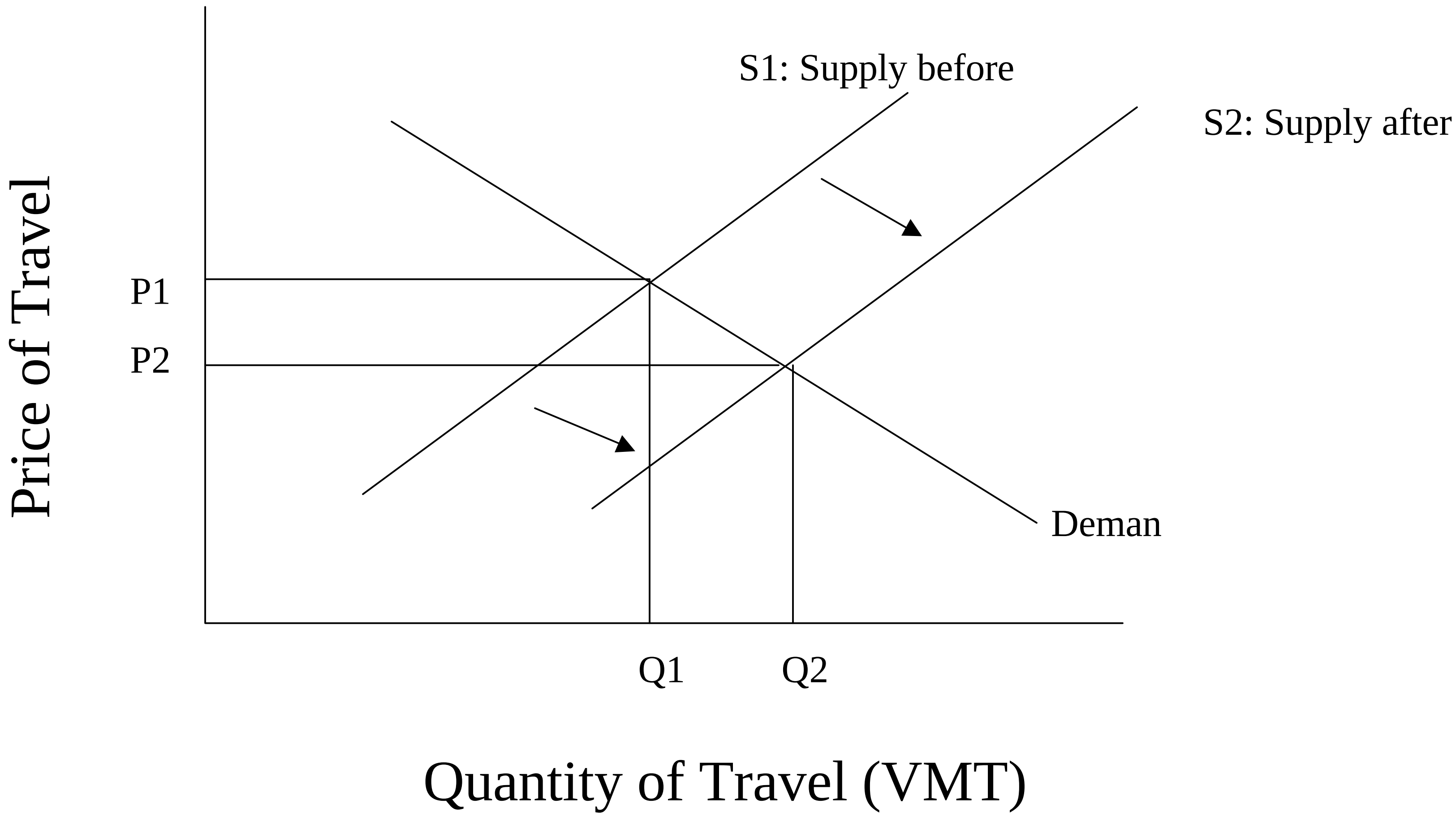

Figure 2

Induced Travel During Period of Underlying Growth in Demand

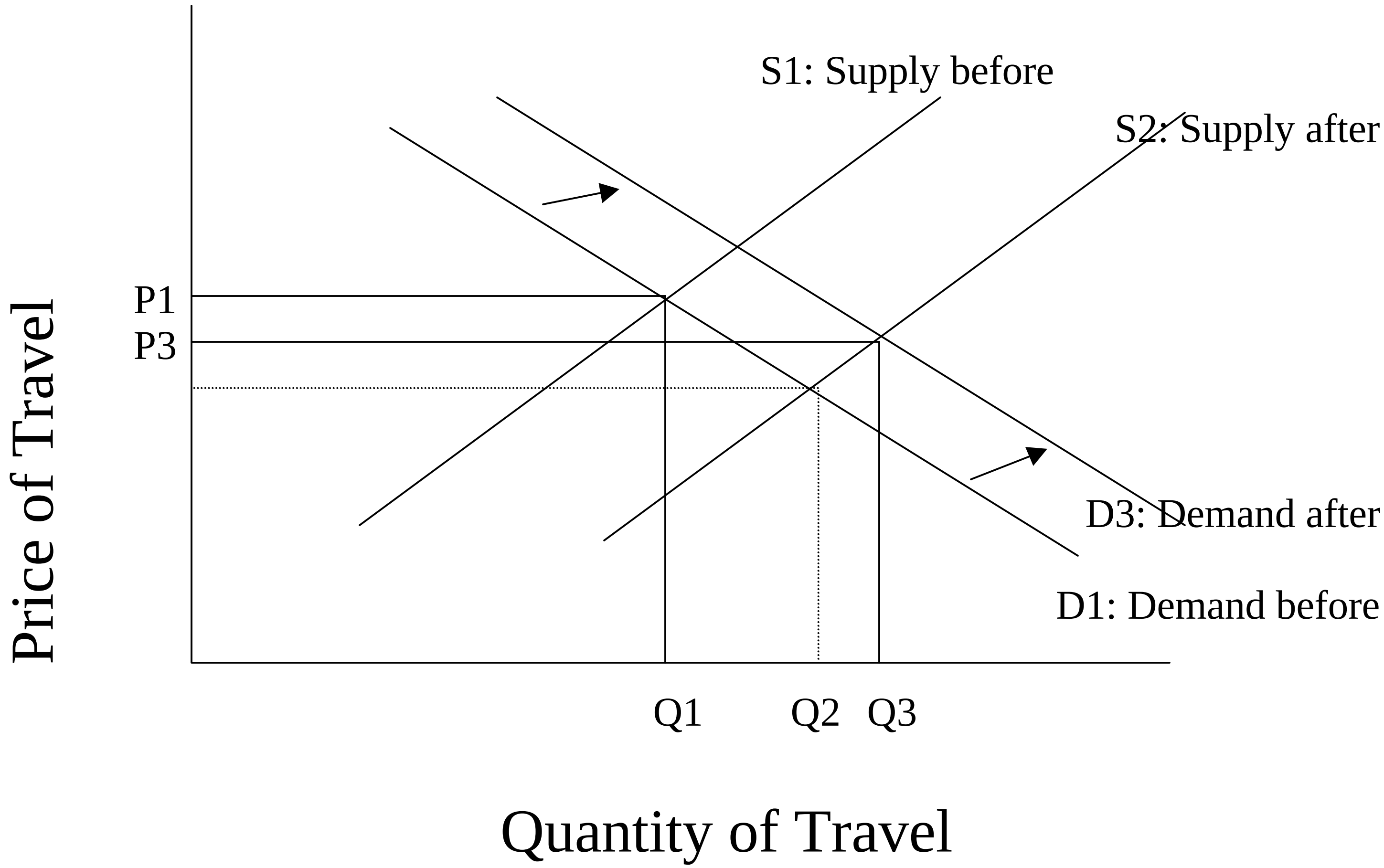

Figure 3:

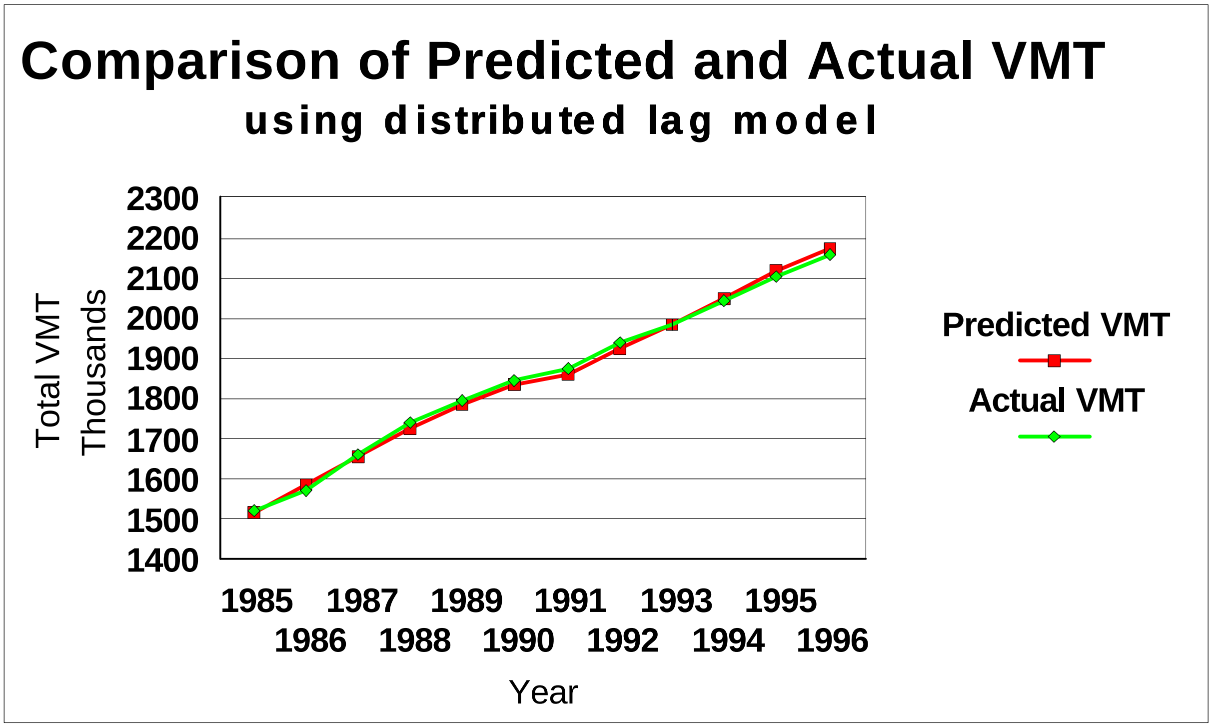
Comparison of Predicted and Actual VMT
using distributed lag model
Total VMT Thousands
2300
2200
2100
2000
1900
1800
1700
1600
1500
1400
1985 1986 1987 1988 1989 1990 1991 1992 1993 1994 1995 1996
Year
Predicted VMT
Actual VMT

Figure 4:

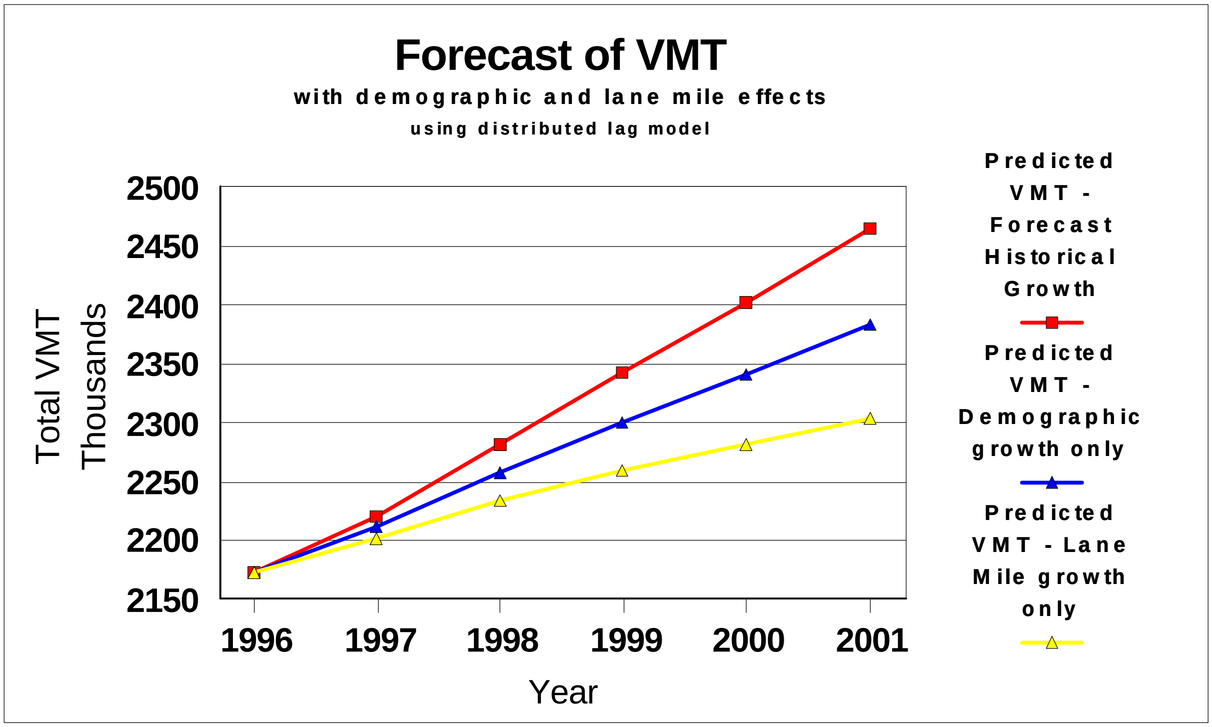
Forecast of VMT
with demographic and lane mile effects
using distributed lag model
Total VMT
Thousands
2500
2450
2400
2350
2300
2250
2200
2150
1996
1997
1998
1999
2000
2001
Year
Predicted VMT - Forecast Historical Growth
Predicted VMT - Demographic growth only
Predicted VMT - Lane Mile growth only

Table 1: Correlation of lane miles with population

	Lane miles	Lane miles per capita
Total non-local lane miles	0.6607	-0.6176
Interstate lane miles	0.7941	-0.7463
Arterial lane miles	0.8007	-0.5903
Collector lane miles	0.5328	-0.5842
Urban interstate lane miles	0.9568	0.2343
Urban arterial lane miles	0.9712	0.1974
Urban collector lane miles	0.9615	-0.0806
Rural interstate lane miles	0.3883	-0.6198
Rural arterial lane miles	0.5151	-0.5857
Rural collector lane miles	0.4303	-0.5499

Table 2: Total VMT regressions

Dependent variable is log of total non-local VMT Lane miles are total non-local lane miles per capita	(A)	(B)	(C)
LN(lane miles per capita)	0.287 (4.167)		
LN(lane miles per capita, 2 year lag)		0.166 (1.794)	
LN(lane miles per capita, 5 year lag)			0.258 (4.043)
LN(population)	1.074 (16.229)	0.989 (10.769)	1.207 (17.003)
LN(per capita income)	1.075 (27.341)	1.116 (25.805)	0.853 (17.879)
LN(cost per BTU of fuel)	-0.126 (-8.025)	-0.192 (-6.517)	-0.126 (-6.030)
Constant	-15.054 (-19.883)	-14.557 (-16.102)	-14.989 (-21.733)
R^2	0.898	0.876	0.891
N	650	550	400

Note that state specific constants are omitted for brevity

Table 3 VMT regressions by road type

Dependent variable is log of VMT by road type Lane miles per capita are by road type	(A)	(B)	(C)	(D)	(E)	(F)	(G)	(H)	(I)
LN(interstate lane miles per capita)	0.627 (10.129)								
LN(interstate lane miles 2 year lag, per capita)		0.549 (8.026)							
LN(interstate lane miles 5 year lag, per capita)			0.043 (0.547)						
LN(arterial lane miles, per capita)				0.632 (14.779)					
LN(arterial lane miles 2 year lag, per capita)					0.268 (5.366)				
LN(arterial lane miles 5 year lag, per capita)						0.167 (2.996))			
LN(collector lane miles, per capita)							0.892 (12.326)		
LN(collector lane miles 2 year lag, per capita)								0.542 (5.132)	
LN(collector lane miles 5 year lag, per capita)									0.149 (0.909)
LN(population)	1.376 (18.543)	1.374 (15.836)	1.123 (10.682)	1.243 (24.661)	1.069 (16.293)	1.249 (15.628)	1.180 (10.927)	0.968 (6.046)	0.569 (2.548)
LN(per capita income)	1.462 (26.969)	1.474 (23.602)	1.399 (16.357)	0.835 (19.216)	0.938 (17.766)	0.805 (12.250)	0.911 (11.846)	0.706 (7.477)	0.332 (2.276)
LN(cost per BTU of fuel)	-0.178 (-8.530)	-0.231 (-5.861)	-0.228 (-6.334)	-0.099 (-5.695)	-0.212 (-5.829)	-0.149 (-5.090)	-0.086 (-2.840)	-0.064 (-0.965)	0.018 (0.274)
Constant	-21.473 (-27.527)	-21.984 (-25.962)	-20.889 (-20.306)	-13.768 (-21.382)	-13.922 (-17.596)	-15.985 (-18.254)	-13.638 (-9.978)	-10.266 (-5.505)	-2.642 (-1.178)
R^2	0.908	0.885	0.844	0.869	0.815	0.817	0.538	0.324	0.112
N	650	550	400	650	550	400	650	550	400

Note that state specific constants are omitted for brevity

Table 4: Seemingly Unrelated Regression by Road Type

	Model 1: no lag			Model 2: 2 year lag			Model 3: 5 year lag		
Dependent variable is log of VMT by road type Lane miles per capita are by road type	(A)	(B)	(C)	(D)	(E)	(F)	(G)	(H)	(I)
LN(interstate lane miles per capita)	0.713 (13.139)								
LN(arterial lane miles per capita)		0.690 (18.991)							
LN(collector lane miles per capita)			0.826 (12.177)						
LN(interstate lane miles 2 year lag, per capita)				0.567 (8.709)					
LN(arterial lane miles 2 year lag, per capita)					0.276 (5.720)				
LN(collector lane miles 2 year lag, per capita)						0.509 (5.023)			
LN(interstate lane miles 5 year lag, per capita)							0.064 (0.812)		
LN(arterial lane miles 5 year lag, per capita)								0.158 (2.848)	
LN(collector lane miles 5 year lag, per capita)									0.134 (0.816)
LN(population)	1.442 (20.423)	1.265 (25.442)	1.118 (10.613)	1.389 (16.329)	1.073 (16.402)	0.933 (5.943)	1.138 (10.834)	1.245 (15.578)	0.555 (2.486)
LN(per capita income)	1.439 (26.832)	0.832 (19.151)	0.901 (11.731)	1.467 (23.728)	0.936 (17.759)	0.706 (7.481)	1.388 (16.241)	0.807 (12.283)	0.335 (2.298)
LN(cost per BTU of fuel)	-0.174 (-8.348)	-0.097 (-5.586)	-0.086 (-2.844)	-0.229 (-5.824)	-0.212 (-5.834)	-0.065 (-0.981)	-0.225 (-6.253)	-0.149 (-5.102)	0.017 (0.265)
Constant	-17.238 (-23.135)	-13.802 (-23.988)	-13.655 (-11.007)	-21.719 (-28.951)	-13.781 (-19.811)	-10.348 (-6.172)	-20.105 (-22.446)	-15.388 (-20.165)	-3.094 (-1.525)
N	650	650	650	550	550	550	400	400	400

Note that state specific constants are omitted for brevity

Table 5: **Seemingly Unrelated Regression by Road Type and Urban/rural area, no lag model**

Dependent variable is log of VMT by road type Lane miles are by road type per capita	urban interstates	urban arterials	urban collectors	rural interstates	rural arterials	rural collectors
LN(urban interstate lane miles, per capita)	0.738 (29.542)					
LN(urban arterial lane miles, per capita)		0.712 (29.225)				
LN(urban collector lane miles, per capita)			0.749 (19.196)			
LN(rural interstate lane miles, per capita)				0.325 (6.526)		
LN(rural arterial lane miles, per capita)					0.610 (16.236)	
LN(rural collector lane miles, per capita)						0.773 (10.612)
LN(population)	1.391 (22.281)	1.119 (20.475)	1.084 (8.725)	0.620 (6.958)	0.979 (15.327)	0.809 (6.440)
LN(per capita income)	1.398 (24.000)	0.731 (14.686)	1.035 (9.092)	1.639 (25.112)	1.162 (22.119)	0.732 (8.485)
LN(cost per BTU of fuel)	-0.144 (-6.314)	-0.077 (-3.823)	-0.006 (-0.135)	-0.199 (-7.635)	-0.026 (-1.261)	-0.134 (-3.934)
Constant	-20.716 (-24.401)	-10.517 (-15.274)	-13.894 (-8.979)	-14.719 (-15.141)	-14.113 (-19.523)	-8.251 (-5.528)
N	632	632	632	632	632	632

Note that state specific constants are omitted for brevity

Table 6 Seemingly Unrelated Regression by Road Type and Urban/rural area, 5 year lag model

Dependent variable is log of VMT by road type Lane miles are by road type, lagged 5 years, per capita	urban interstates	urban arterials	urban collectors	rural interstates	rural arterials	rural collectors
LN(urban interstate lane miles, lagged 5 years, per capita)	0.141 (2.099)					
LN(urban arterial lane miles, lagged 5 years, per capita)		0.097 (2.732)				
LN(urban collector lane miles, lagged 5 years, per capita)			0.004 (0.049)			
LN(rural interstate lane miles, lagged 5 years, per capita)				-0.098 (-1.842)		
LN(rural arterial lane miles, lagged 5 years, per capita)					0.336 (3.322)	
LN(rural collector lane miles, lagged 5 years, per capita)						0.117 (0.620)
LN(population)	1.795 (13.181)	1.302 (13.212)	2.274 (8.436)	0.265 (2.414)	1.124 (7.005)	-0.500 (-1.799)
LN(per capita income)	1.476 (12.320)	0.720 (8.505)	0.297 (1.286)	1.354 (14.949)	0.871 (7.484)	0.508 (2.833)
LN(cost per BTU of fuel)	-0.365 (-6.613)	-0.226 (-5.846)	-0.120 (-1.127)	-0.123 (-3.089)	-0.008 (-0.158)	-0.001 (-0.011)
Constant	-30.664 (-19.394)	-16.278 (-15.097)	-26.639 (-9.625)	-9.511 (-9.194)	-14.369 (-10.310)	8.662 (3.409)
N	387	387	387	387	387	387

Note that state specific constants are omitted for brevity

Table 7: Total VMT regression: distributed lag models

Dependent variable	LN (non-local VMT)	LN (non-local VMT per capita)
LN(lane miles per capita)	0.119 (2.680)	0.128 (4.250)
LN(VMT lagged one year)	0.674 (27.226)	-
LN(VMT per capita lagged one year)	-	0.690 (27.928)
LN(population)	0.304 (5.851)	-
LN(per capita income)	0.376 (9.982)	0.321 (8.479)
LN(cost per BTU of fuel)	-0.048 (-4.017)	-0.049 (-4.124)
Constant	-4.316 (-6.734)	-3.995 (-8.927)
R^2	0.953	0.913
N	600	600
Short run elasticity	0.119	0.128
Long run elasticity	0.365	0.413

Note that state specific constants are omitted for brevity

Table 8 Seemingly Unrelated Regression by Road Type and Urban/rural area: distributed lag model, per capita VMT

Dependent variable is log of VMT per capita by road type Lane miles are by road type per capita	urban interstates	urban arterials	urban collectors	rural interstates	rural arterials	rural collectors
LN(VMT per capita, lagged one year)	0.492 (19.878)	0.379 (13.303)	0.529 (20.056)	0.675 (30.810)	0.487 (16.753)	0.653 (21.715)
LN(urban interstate lane miles, per capita)	0.427 (16.784)					
LN(urban arterial lane miles, per capita)		0.491 (17.794)				
LN(urban collector lane miles, per capita)			0.512 (14.990)			
LN(rural interstate lane miles, per capita)				0.258 (9.204)		
LN(rural arterial lane miles, per capita)					0.362 (11.382)	
LN(rural collector lane miles, per capita)						0.422 (8.774)
LN(per capita income)	0.714 (11.730)	0.474 (10.269)	0.404 (4.965)	0.464 (9.086)	0.601 (11.941)	0.272 (4.003)
LN(cost per BTU of fuel)	-0.085 (-4.245)	-0.049 (-2.403)	-0.027 (-0.685)	-0.065 (-3.609)	-0.036 (-1.847)	-0.036 (-1.181)
Constant	-7.532 (-10.402)	-5.448 (-9.818)	-4.092 (-4.369)	-4.942 (-8.864)	-7.162 (-12.165)	-3.440 (-4.915)
N **Long run elasticities**	583	583	583	583	583	583
Lane miles per capita	0.841	0.791	1.087	0.794	0.706	1.216
Personal income	1.406	0.763	0.858	1.428	1.172	0.784
Gasoline price	-0.167	-0.079	-0.057	-0.200	-0.070	-0.104

Note that state specific constants are omitted for brevity

Table 9 Seemingly Unrelated Regression by Road Type and Urban/rural area: distributed lag model

Dependent variable is log of VMT by road type Lane miles are by road type per capita	urban interstates	urban arterials	urban collectors	rural interstates	rural arterials	rural collectors
LN(VMT, lagged one year)	0.464 (17.981)	0.370 (12.915)	0.528 (20.251)	0.669 (30.774)	0.485 (16.658)	0.649 (21.658)
LN(urban interstate lane miles, per capita)	0.439 (17.136)					
LN(urban arterial lane miles, per capita)		0.498 (18.002)				
LN(urban collector lane miles, per capita)			0.513 (15.097)			
LN(rural interstate lane miles, per capita)				0.234 (6.473)		
LN(rural arterial lane miles, per capita)					0.369 (10.621)	
LN(rural collector lane miles, per capita)						0.407 (6.726)
LN(population)	0.625 (9.561)	0.652 (10.279)	0.690 (6.645)	0.250 (4.057)	0.509 (8.159)	0.307 (2.950)
LN(per capita income)	0.748 (12.227)	0.489 (9.788)	0.328 (3.545)	0.531 (9.858)	0.630 (11.450)	0.313 (4.387)
LN(cost per BTU of fuel)	-0.085 (-4.191)	-0.047 (-2.308)	-0.019 (-0.478)	-0.064 (-3.590)	-0.035 (-1.746)	-0.033 (-1.106)
Constant	-9.149 (-9.479)	-5.908 (-7.864)	-6.219 (-4.907)	-4.702 (-6.574)	-7.349 (-10.093)	-3.350 (-2.786)
N **Long run elasticities**	583	583	583	583	583	583
Lane miles per capita	0.819	0.790	1.087	0.707	0.717	1.160
Population	1.166	1.035	1.462	0.755	0.988	0.875
Personal income	1.396	0.776	0.695	1.604	1.223	0.892
Gasoline price	-0.159	-0.075	-0.040	-0.193	-0.068	-0.094

Note that state specific constants are omitted for brevity

Table 10 Correlations between Lane Mile and Population Growth Variables

Correlation coefficients	Population Growth
Growth in Lane miles, urban interstates	0.1966
Growth in Lane miles, urban arterials	0.1591
Growth in Lane miles, urban collectors	0.1366
Growth in Lane miles, rural interstates	-0.0325
Growth in Lane miles, rural arterials	0.0643
Growth in Lane miles, rural collectors	-0.0361

Table 11 Seemingly Unrelated Regression by Road Type and Urban/rural area: growth model

Dependent variable is growth in VMT by road type	urban interstates	urban arterials	urban collectors	rural interstates	rural arterials	rural collectors
Growth in urban interstate lane miles	0.647 (18.936)					
Growth in urban arterial lane miles		0.642 (18.083)				
Growth in urban collector lane miles			0.780 (18.916)			
Growth in rural interstate lane miles				0.560 (11.037)		
Growth in rural arterial lane miles					0.578 (10.229)	
Growth in rural collector lane miles						0.646 (7.502)
Growth in population	0.922 (2.988)	1.124 (3.436)	-0.207 (-0.353)	0.197 (0.745)	0.425 (1.307)	0.574 (1.235)
Growth in per capita income	0.569 (5.247)	0.307 (2.655)	-0.059 (-0.284)	0.591 (6.331)	0.513 (4.473)	0.196 (1.193)
Growth in cost per BTU of fuel	-0.035 (-1.811)	-0.001 (-0.051)	0.409 (1.095)	-0.013 (-0.796)	0.001 (0.042)	0.001 (0.027)
Constant	0.009 (0.658)	0.015 (1.037)	0.012 (0.467)	0.029 (2.501)	0.009 (0.625)	0.004 (0.200)
N	583	583	583	583	583	583

Note that state specific constants are omitted for brevity

Table 12: Forecast using Model in Table 5 (SURE model)

VMT FORECAST IN 2001	VMT urban interstates	VMT urban arterials	VMT urban collectors	VMT rural interstates	VMT rural arterials	VMT rural collectors	TOTAL VMT	Annualized growth rate in VMT
HISTORIC GROWTH IN DEMOGRAPHIC AND LANE MILE VARIABLES	616236	759347	147273	262883	424933	250887	2461559	2.68%
forecasted growth rate	3.97%	2.46%	2.89%	2.49%	2.42%	0.86%	2.68%	
DEMOGRAPHIC GROWTH ONLY	583396	717622	138810	263236	421576	253180	2377820	1.97%
forecasted growth rate	2.84%	1.31%	1.68%	2.52%	2.26%	1.04%	1.97%	
LANE MILE GROWTH ONLY	548074	710181	134396	230600	382622	238341	2244213	0.79%
forecasted growth rate	1.56%	1.10%	1.02%	-0.16%	0.29%	-0.17%	0.79%	

Table 13: Forecasts using Model in Table 9 (Distributed Lag Model)

HISTORIC GROWTH IN DEMOGRAPHIC AND LANE MILE VARIABLES	VMT urban interstates	VMT urban arterials	VMT urban collectors	VMT rural interstates	VMT rural arterials	VMT rural collectors	TOTAL VMT	Annualized growth rate in VMT
1997	530406	691021	131473	237934	387767	242383	2220984	
1998	551137	709297	135652	243543	397726	244491	2281846	2.74%
1999	571006	727704	140090	249278	407383	246618	2342078	2.69%
2000	590887	746539	144768	255143	417009	248749	2403096	2.66%
2001	611240	765949	149712	261149	426748	250890	2465688	2.65%
forecasted growth rate	3.61%	2.61%	3.30%	2.35%	2.42%	0.87%	2.65%	
DEMOGRAPHIC GROWTH ONLY								
1997	527154	685774	130515	237979	387408	242603	2211433	
1998	542720	696461	133014	243660	396795	245075	2257727	2.09%
1999	556215	706084	135242	249482	405743	247656	2300422	1.99%
2000	568843	715367	137298	255442	414559	250293	2341802	1.93%
2001	581198	724599	139263	261544	423404	252968	2382976	1.89%
forecasted growth rate	2.47%	1.39%	1.64%	2.39%	2.25%	1.05%	1.89%	
LANE MILE GROWTH ONLY								
1997	524646	685558	130669	236112	383682	241480	2202147	
1998	536455	696060	133556	238587	387383	242091	2234132	1.45%
1999	545570	705578	136383	240237	389600	242326	2259694	1.30%
2000	553502	714861	139225	241323	391094	242299	2282304	1.20%
2001	560990	724213	142148	242028	392249	242101	2303729	1.13%
forecasted growth rate	1.69%	1.38%	2.13%	0.62%	0.55%	0.06%	1.13%	

Table 14: Forecasts using Model in Table 11 (Growth model)

VMT FORECAST IN 2001	VMT urban interstates	VMT urban arterials	VMT urban collectors	VMT rural interstates	VMT rural arterials	VMT rural collectors	TOTAL VMT	Annualized growth rate in VMT
HISTORIC GROWTH IN DEMOGRAPHIC AND LANE MILE VARIABLES	605338	770554	153890	276134	423526	261842	2491285	2.92%
forecasted growth rate	3.60%	2.76%	3.80%	3.50%	2.35%	1.73%	2.92%	
DEMOGRAPHIC GROWTH ONLY	578081	733393	146235	276669	420257	263412	2418047	2.31%
forecasted growth rate	2.65%	1.75%	2.74%	3.54%	2.19%	1.85%	2.31%	
LANE MILE GROWTH ONLY	562111	719381	155525	261885	399913	252046	2350861	1.73%
forecasted growth rate	2.08%	1.36%	4.02%	2.41%	1.19%	0.95%	1.73%	